The Impact of Development Aid on Education and Health

The Impact of Development Aid on Education and Health: Survey and New Evidence for Low-Income Countries from Dynamic Models[1]

This paper has four messages. First, a literature review shows that panel data models including lagged dependent variables lead to statistically significant, favourable results for at least one form of aid unless only commitment data are used. Second, in our own analysis we find that growth rates or levels of aid per capita have statistically significant, favourable effects on growth rates rather than on levels of life expectancy and illiteracy. Third, for the growth rate of illiteracy we find a strong role of polynomial distributed lags, helping to explain the great diversity of aid results found in the literature. Fourth, in simulations, both effects are small in terms of growth rates in the short run but cumulate over time to non-negligible amounts.
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1. Introduction and literature review

The debate on the effectiveness of aid traditionally focussed on the link between aid and growth, and from there has moved on to institutional aspects of donor and receiving countries. This article's empirical analysis is concerned with the effects of aid on the social and poverty dimensions, about which little was known until recently (White 2001) but some progress has been made during recent years. The focus will be on education and health, which are vital to the poor, who mostly have to rely on the sale of their labour to generate income.

The reason for writing this article is that the literature on the effects of aid on education and health is as contradictory in terms of results as that of aid and growth or aid and accumulation. Therefore we want to review the literature to try to find out why it is contradictory and which type of empirical investigation produces which type of results. In this article we therefore first provide a survey of the literature explaining which properties of empirical research methodology lead to which type of results regarding the effects of aid on health and education.

In order to test the findings from the literature review, we carry out a panel data analysis of the impact of development aid per capita of the receiving country on illiteracy

[1] Useful suggestions of an anonymous referee are gratefully acknowledged. I am grateful to Christof Gross for cooperation in the first phase of this paper. He provided the first data set used here and contributed to the text. Recent developments in dynamic panel data econometrics required reworking the estimates in the second phase.

and life expectancy. In particular, we go beyond the literature in that we investigate the role of lag structures inducing different long- and short-term effects, and find that they are very important indeed. The data are described in section 2; the econometric methodology in section 3; the empirical results in section 4; in section 5 we use polynomial distributed lags; in section 6 we run simulations for the quantification of the effects of aid; and section 7 concludes.

In the following we briefly summarize the results of the literature in order to show how contradictory it is in terms of results. More detailed information is available in Table 1. At the end of this section we use this information to offer a more structured interpretation of the literature that indicates that dynamic panel data analysis using data on disbursed aid finds favourable effects of aid on education and health, whereas the static regressions and those using commitment data have mixed results.

<TABLE 1 near HERE>

Boone (1996) finds a negative effect of the level of the aid/GNP ratio on the growth rates of infant mortality and primary schooling, and a positive effect on the change of life expectancy. However, all effects are insignificant, possibly because a large set of control variables is employed, which may not only pick up all indirect effects but also cause collinearity, in particular with GDP variables. Burnside and Dollar (2000) show that overall aid, interacted with a policy index, reduces infant mortality unless the policy index is zero. Gomanee *et al*. (2005a) find a negative effect of aid on mortality, with stronger and more significant effects for poorer countries in a quantile regression. Gomanee *et al*. (2005b) confirm these results using fixed-effects estimation and extend them to middle-income countries. Gross (2003) finds favourable effects of aid per capita on illiteracy and life expectancy. He uses levels of all variables. For literacy this leads to a coefficient of the lagged dependent variable larger than unity, indicating an unstable difference equation or a unit root. When a time trend is used instead, the coefficient is below unity, but a time trend implies that the variables grow beyond all more or less natural limits such as zero or 100 for literacy or slightly higher values for life expectancy. This requires a more careful look at the lag structure of lagged dependent variables, one of the contributions of this paper. Bhaumik (2005) finds for African countries that World Bank assistance has a significantly negative effect on infant mortality and significantly positive effects on completing primary education, with all variables in first differences by assumption. However, when looking at mortality before the fifth birthday and youth literacy, a 15% significance level applies; for progressing to fifth grade results become insignificant also at the 15% level and have unexpected signs. Michaelowa (2004) finds a positive effect of education aid (also when taken per unit of GDP or per capita) on primary enrolments, which is confirmed by Birchler and Michaelowa (2013) in connection with effects on the related facilities and teachers, and an incentive effect from secondary schooling; they do not find a positive effect on achievements in tests. Masud and Yontcheva (2005) find that bilateral aid and NGO aid, both in per capita terms, have no impact on illiteracy, but NGO aid has an impact on infant mortality as long as GDP per capita is not in the regression – the latter may cause collinearity problems as NGO aid goes to countries with more mortality, which are poorer countries. There is also no indirect effect of these forms of aid via government expenditure on health or education. Fielding *et al*. (2006) develop a simultaneous equations model and find favourable direct and equilibrium effects of overall aid per capita on infant mortality and schooling; the effect on schooling is insignificant, however, and its equilibrium effect small. Wolf (2007) investigates the impact of aid on sanitation, water, infant and under-5 mortality, primary completion rates and youth literacy. Four aid variables are used simultaneously: aid/GNI and its coefficient of variation; and aid earmarked for water and its interaction with control of corruption. Aid/GNI has unfavourable or insignificant effects. The volatility indicator has favourable effects on water, sanitation and mortality. Earmarked aid has favourable effects only on health and education but not on water and sanitation. Interaction with control of corruption has a significantly favourable effect only for water if a federalism indicator is included, but not otherwise. Williamson (2008) finds that aid per capita earmarked for the health sector has no impact on five health indicators in a fixed-effects estimate using five- and three-year averages of data for 208 countries. In contrast, Mishra and Newhouse (2009), using lagged dependent variables, find a reduction of infant mortality through health aid per capita or per unit of GDP, but no such effect of overall aid. Dreher *et al*. (2008) find a positive effect of per capita aid for education on primary school enrolment, but not for total disbursed aid. Gyimah-Brempong and Asiedu (2008) find favourable effects of earmarked aid (per capita and per unit of GDP) on primary completion rates and infant mortality. Chauvet *et al*. (2008) find that health aid per capita reduces infant and child mortality if health aid per capita interacted with per capita income is added as a control variable. D'Aiglepierre and Wagner (2010) find a significantly positive effect of aid per capita earmarked for education on enrolments and also a favourable impact on the achievement variables gender parity in enrolment, the primary completion rate and the repetition rate. Findley *et al*. (2010) find a negative or insignificant effect of education aid commitments on average years of schooling using propensity score matching. Wilson (2011) finds no effect of committed development assistance for health on infant mortality. Christensen *et al.* (2011) find a positive effect of bilateral aid commitments on primary enrolments when countries make it a condition on recipients to control corruption. Ziesemer (2011) finds a positive direct impact of the aggregate aid/GDP ratio on literacy, and a positive indirect effect of aid via public expenditure on education, both as a share of GDP. Arndt *et al.* (2011) find a positive effect of aggregate aid per capita on life expectancy in a cross-section regression only when using inverse probability weighted least squares (IPWLS), but not when using OLS or limited information maximum likelihood (LIML). Gillanders (2011) reports positive impulse responses from shocks of aid per capita on the growth rate of life expectancy in a PVAR (panel vector autoregressive) model; they are stronger if countries are democratic and have good institutions. Burguet and Soto (2012) find that infectious-disease aid (IDA) per capita reduces under-5 mortality mainly through malaria and STD/HIV control, but also due to the other IDA components. Feeny and Quattara (2013) find significantly positive effects of health aid as a percentage of GDP on rates of immunization for measles and DPT (diphtheria–pertussis–tetanus). Mukherjee and Kizhakethalckal (2013) show that health aid per capita reduces infant mortality (in a highly non-linear way) if primary school completion rates are above 38%, which is outside the lowest quintile. This happens mostly through nutritional aid and perhaps prenatal care. Pickbourn and Ndikumana (2013) estimate the effect of disbursed health and education aid on maternal mortality and health and education indices. Whenever they employ lagged dependent variables they find significantly positive results. Otherwise the results are mixed. Yogo and Mallaye (2015) show that health aid per capita increases life expectancy and reduces child mortality and HIV in a sample of 34 countries in sub-Saharan Africa. Yogo and Mallaye (2014) show a statistically significant positive effect of disbursed education aid on primary completion rates in sub-Saharan Africa. Hudson (2015) finds that social infrastructure aid, defined as the sum of aid for education, health, water and government, has a positive impact on primary school completion rates, whereas other forms of aid do not. This chronological survey emphasizes the diversity of variables and results.

A look at the data and estimation methods shown in Table 1 suggests the following conclusions. Lagged dependent variables and dynamic panel data methods are used in many papers (see Table 1, column 7). Interestingly, with the exception of Wilson (2011), using commitment data, all the papers using lagged dependent variables and the adequate dynamic panel data methods find positive effects of some form of aid on the social indicators considered, whereas the evidence from the other papers is much more mixed.

Although several authors find that regressions with lagged dependent variables – in particular when using GMM – tend to find a low number of significant regressors, but aid turns out to be significant. To the extent that there is some fungibility of aid (Feyzioglu *et al*. 2008; Morrissey 2015), it may be mitigating the effects of aid but is not completely undermining them when dynamic panel data methods are used.

Moreover, Table 1, column 4 shows that, for earmarked aid, use of commitment data mostly leads to insignificant results; use of disbursement data mostly leads to significantly favourable results. Besides enrolments (Riddel 2012), primary completion rates and literacy have also been improved through aid.

The channels through which aid affects social and poverty variables according to the literature discussed are the following. Aid affects the HDI (Human Development Index) social and poverty indicators (i) directly and (ii) indirectly via growth (Collier and Dollar 2002), and (iii) via public expenditure (Mosley *et al*. 2004; Gomanee *et al*. 2005a; Mishra and Newhouse 2009), (iv) through interactions among several social indicators such as female education reducing infant mortality and thereby life expectancy (Fielding *et al*. 2006; Feeny and Quattara 2013; Mukherjee and Kizhakethalckal 2013; Yogo and Mallaye 2015); and (vi) via a combination of some of these channels affecting infant mortality, primary enrolment or literacy either via multiple equation approaches (Ziesemer 2011) or by not limiting the specification to certain channels as most papers do.

In order to avoid the complications of large systems of equations, we do not distinguish the different channels but rather estimate the total effect of aid with and without control variables, which mostly turn out to be insignificant.

We do not use earmarked aid for several reasons: first, its favourable effects have now been shown repeatedly, provided it is also disbursed; second, budget aid may also be used to target the social indicators without being earmarked by donors (Wolf 2007; d'Aiglepierre and Wagner 2010); third, because earmarked aid may underestimate the indirect effects after the first round of spending; and fourth, there is an increasing share of budget aid in total aid (Wolf 2007).

2. Data

We work with three data sets. All data have been taken from the World Bank's World Development Indicators. All samples cover 65 low-income countries as defined by the World Bank in 2003 (see Appendix A). It is well known that low-income countries show different effects of aid on education than middle- and high-income countries (see for example Asiedu and Nandwa 2007). However, there is no other famous variant of heterogeneity that suggests further disaggregation. Looking at poorer continents like sub-Saharan Africa (Yogo and Mallaye 2015) is of course an alternative, similar to our look at poor countries that trades off regional similarities with greater income heterogeneity within the region. In the first data set observations are available for the years 1960–2001 and are arranged in five-year averages of eight periods from 1961–1965 to 1996–2000. This has the advantage of smoothing the data, accounting for single years of no availability, and also for the fact that effects often do not materialize immediately but with an unknown lag. The investigation with five-year data shortens the time dimension and emphasizes the cross-country dimension. Second, we also investigate these data using the yearly data until 2001, thereby shifting emphasis to the end where coverage is better; as the time dimension becomes larger, emphasis also shifts away from the cross-section to the time-series dimension and becomes more in line with policy advice hoping for intertemporal effects. The third data set aims to employ the recent good coverage with yearly data from 1960 to 2010 from World Development Indicators 2012, and therefore puts even more emphasis on the time dimension. Using three different data sets with different overall length and different lengths of period should be sensitive enough to avoid the impression that results are obtained only accidentally and could vanish when some observations are added.

In order to examine the relationship between aid and education and health, respectively, the following dependent variables were used as proxy variables (see Appendix A, Table A.1 for details):

- *Ill*: a percentage measure of the total adult population (15 and above) that is not literate. The data in Table A.1 show that there is a slight fall in illiteracy over time when comparing panel (b) with panel (c).
- *Life*: total population's average life expectancy at birth in years. The data span all 65 countries, with only a few observations missing. There is only a slight increase in life expectancy over time when comparing Table A.1 panel (b) with panel (c)).

The illiteracy rate is used to proxy for education, while life expectancy at birth is taken as representative of the health condition of the population. These indicators have the following advantages. In a developmental context, education during the last decennia often meant primary schooling because the ability to read and write is crucial for the poor to escape poverty, and as a basis for higher levels, which may also help to alleviate poverty. Therefore the illiteracy rate is an important and poverty-relevant indicator of education. The health condition of a population can be expressed by several factors, such as child mortality, incidence of AIDS and other diseases, number of doctors or hospital beds per 1000 persons. All of this information, especially under-5 mortality, affects life expectancy at birth, which is an aggregate measure of health.

The following development indicators are thought to represent the wider poverty concept and were related to the following independent variables:[2]

- *Aid/pop*: aid per head in constant 1995 (2009) US dollars as the original current US dollar series was deflated by the OECD's deflators for resource flows from Development Assistance Committee members and indexed to 1995 (2009). It is expected that aid will have a negative coefficient in the estimation of the growth rate of illiteracy and a positive one in the regression of life expectancy. A comparison of panels (b) and (c) in Table A.1 shows that aid per capita has grown strongly in recent years.
- *gdp*: GDP per capita in constant 1995 (2000) US dollars. It is assumed that it has a significant impact on the dependent variables analogous to that of aid.
- *health*: total health expenditure expressed as a percentage of GDP. Data on health spending are available for the period after 1985. Naturally, it is expected that health spending has a positive effect on life expectancy.
- *nineties*: dummy variable: 1 for more recent periods since 1991 and zero otherwise. The nineties dummy was introduced in order to be interacted with aid. It was included because several authors and aid agencies claimed that the manner of giving aid by donors had become more effective (see Hudson and Mosley 2001), in part due to the implementation of the findings of the effectiveness debate (Mishra and Newhouse 2009). Constructed that way, it should capture any improvements in aid policies in that decade, e.g. through policy conditionality or tighter selectivity.
- *rural*: proportion of the population living in rural areas. This variable is aimed at capturing some of the country-specific characteristics. Assuming that a high proportion of rural population has detrimental effects on literacy (as in Masud and Yontcheva 2005) and life expectancy, this variable should be important unless the relations are spurious because driven by third factors. Furthermore, data coverage

[2] As military expenditure had no effect on any of our regressions, we do not include it in the data. The share of public expenditure on education expressed as a percentage of GDP only matters in the preliminary fixed-effects estimates of Appendix Table A.2. Also a dummy for sub-Saharan Africa ultimately plays no role in our results.

is almost perfect. Surprisingly, though, the variable is not falling on average, as it has roughly the same mean in the three data sets of Table A.1.

- *PEE*: public expenditure on education as a share of GDP.

As five-year averages mask variation, reduce the time dimension and have other disadvantages (Attanasio *et al*. 2000), we use the yearly data first until 2001 and then until 2010.

3. Methodology

We use the system GMM (GMMSYS), fully modified OLS (FMOLS), and two-stage least squares (2SLS). We fully explain system GMM and how we use it in the following paragraph because we use it repeatedly and it is less well known.

Without lagged dependent variables, no distinction between short-term and long-term effects can be made and the dynamics in the panel data is not used (Smith and Fuertes 2010). If one wants to emphasize the dynamics, it is important that policy takes time to have effects and five-year lags seem more plausible then ten-year lags (Mishra and Newhouse 2009). We emphasize the role of fixed effects, lagged dependent variables and first-differences specifications for all variables. We find first differences to be the relevant way of using the data in system GMM after extensive consideration of several lagged dependent variables and the size of their coefficients. Similarly, Mishra and Newhouse (2009) find that their lagged dependent variable has a coefficient of unity and report in a footnote that estimation in first differences gives the same result for aid. However, this may point to a fundamental misspecification and therefore deserves extensive analysis. Moreover, when taking logs of data as introduced above in terms of differences, fixed effects turn out not to be redundant, whereas the use of the system GMM model assumes exactly that for level variables. We also avoid collinearity by not employing GDP levels on the right-hand side, implying that we do not treat direct and indirect effects via GDP per capita separately, because the literature on this aspect casts doubt on that procedure.[3] We could use several other control variables such as GDP per capita, infant mortality, specific forms of aid, but they are under suspicion of collinearity, which has an impact on significance and sign, and this should be avoided by taking out

[3] Collier and Dollar (2002) take the opposite view. They assume that aid reduces poverty only through growth at a given distribution, and even more so under good policies. Fielding *et al.* (2006) discuss many examples of two-way causality of GDP per capita with other variables related to health and education, and collinearity has been a widely discussed topic in growth regressions. In Yogo and Mallaye (2015) GDP variables are statistically insignificant.

the less significant variables in order to avoid overfitting (Greene 2008).[4] Given the panel structure of the data, pooled estimation techniques have to be used. The basis for the analysis of panel data in the case of lagged dependent variables is given by the equation

$$y_{it} = \gamma y_{i,t-1} + \beta_0 + \beta_1 x_{it1} + \ldots + \beta_k x_{itk} + a_i + b_t + u_{it} \qquad \textbf{(1)}$$

Here *i* denotes cross-sections, *t* denotes periods, and 1, ..., *k* denotes the explanatory variables other than the lagged dependent variable. The regressors x_{it} cover the effects, which are variable over time, whereas the a_i term represents the unobserved or fixed effects for cross-section units and b_t those of periods of time. The country-specific effects may be correlated with the regressors. For all the fixed-effects versions of our regressions we have tested for the redundancy of fixed effects. Fixed effects vanish only when the left-hand-side variables are changes of growth rates. A Hausman test also indicates in all cases that random effects are not a superior conceptual alternative. The fixed-effects model, however, is also not without problems. The lagged dependent variable implies that a fixed-effects estimate would underestimate its coefficient, γ, with an expected bias of the order $1/T$ if the lagged dependent variable is the only regressor (Baltagi 2008; Greene 2008); this is smaller when an additional endogenous regressor has a low autocorrelation coefficient, but larger if an additional endogenous regressor has a high autocorrelation coefficient (Bruno 2005). Using OLS after dropping fixed effects by assumption when they are not redundant would lead to overestimation of γ (see also Durlauf *et al*. 2005). The true value, between those from fixed effects and OLS, could be obtained using the system GMM approach. We use this approach in the way explained in Ziesemer (2012).

In the case of omitted variables and spatial correlation there may be cross-section dependence, which may bias the estimates (Smith and Fuertes 2010; Sarafides and Wansbeek 2010). Whether or not one has a bias also depends on the parameter values and the time dimension *T*. One way out is a GMM difference estimator that takes variables as deviations from time-specific averages (see Sarafides and Wansbeek 2010, section 5.2). We use it when GMMSYS fails in regard to cross-section dependence as tested by the Pesaran CD statistic.

[4] According to Masud and Yontcheva (2005), NGO aid, infant mortality and GDP per capita are collinear. Fielding *et al.* (2006) use the sub-title 'Correlated impacts on health, wealth, fertility and education', and deal with collinearity. Chatelain and Ralf (2012) explore the collinearity issue econometrically and emphasize the danger of using quadratic terms, which may oversize parameters. We avoid this except for some of the preliminary regressions of Table A.1.

The underlying question is whether aid is effective in combating illiteracy and improving life expectancy. Therefore the equations to be estimated are, in the first instance:

$$d(\log(ill_{it})) = \varphi d(\log(ill_{i,t-x})) + \alpha_0 + \alpha_1 d(\log(aid))_{it}$$
$$+ \alpha_2 nineties * \log(aid)_{it} + a_i + b_t + u_{it} + controls \qquad (2)$$

$$d(\log(life_{it})) = \delta d(\log((life_{i,t-1})) + \xi_0 + \xi_1 d((\log(aid))_{it}$$
$$+ \xi_2 nineties * d(\log(aid))_{it} + c_i + f_t + \varepsilon_{it} + controls \qquad (3)$$

On the left-hand side of these equations we have the growth rates of illiteracy and life expectancy. On the right-hand side we have lags of the dependent variables and the growth rates of aid per capita with and without interaction with the dummy for the 1990s. In addition, we have fixed effects for countries and periods and a residual. We indicate verbally in the equations that we might add control variables. In order to make a judgement on aid effectiveness in terms of the dependent variables, the coefficients on log(*aid*) and on the interaction term *nineties**log(*aid*) are of primary interest, either in levels or in first differences. In order to distinguish the effect of aid from the idea that illiteracy and life expectancy are improving anyway, and would so without aid, we add a lagged dependent variable, which turns the regression equation into a difference equation, which could in principle have its own dynamic process even without aid (Wilson 2011) but aid or its changes can speed up or slow down this process. The challenge then is to show that aid can speed up this process. Including or dropping time dummies as a remedy against cross-sectional dependence is indicated in the notes to the tables. A country-specific intercept allows us to capture some heterogeneity and unobserved variables. All the other explanatory variables described above were added when trying to find a good specification.

Finally, in order to avoid results being driven by outliers (Chatelain and Ralf 2014), we run bi-variate nearest-neighbour-fit or kernel-fit regressions of the aid variables on the dependent variables~~, both as defined in Tables 2–4~~. These regressions can have changing slopes that may be different in the region of outliers than where the most observations are.

As our third data sample has almost thirty observations in the time dimension, the panel here is not really as short as those for which GMMSYS has been developed. It also is just close to the area of long panels. Therefore we also try using the method of fully modified OLS (FMOLS) developed for long panels (see Baltagi 2008: chapter 12). This uses a data transformation that deals with endogeneity, contemporaneous correlation and serial correlation for variables de-meaned by their country-specific averages, thereby taking into account fixed effects. Therefore one has neither to test for endogeneity or exogeneity, nor find instrumental variables.

Finally, in order to explore the lag structure of the effects of aid, we apply polynomial distributed lags in section 5, which are well explained in econometric textbooks.

Before applying adequate methods, however, one has to find the adequate specification. Experimentation with logs, lags, squares and differences of the fixed-effects estimator leads us to the result that data should be taken in logs at least for the life expectancy variable, but less clearly so for illiteracy. Moreover, data should mostly be taken in terms of first differences when used in the approach of equation (1) because fixed effects have turned out to be still present after taking differences. Having tested that lags not appearing in the regressions are not significant and therefore excluded, they can be used as instruments. The tables and their results indicate which specification was most successful in regard to logs, lags, squares and differences.

4. Estimation Results

In order to find a good specification we first run fixed-effects estimates with both five-year-averaged data and yearly data (see Appendix A, Table A.2). Results for the system GMM and the corresponding OLS and fixed-effects estimates in order to compare the coefficients for the lagged dependent variable are reported here for the longer sample.[5] Results for the shorter samples are reported in Ziesemer (2012).

<TABLE 2 near HERE>

GMM and FMOLS results for life expectancy and illiteracy, 1960–2010

Table 2 shows two lagged dependent variables in all equations; the sum of their coefficients obeys the rule that they are higher in regressions (2) and (6) for GMMSYS than for the corresponding fixed-effects estimates (1) and (5) and lower than for the OLS estimates (3) and (7). For FMOLS this is the case for the life expectancy regression but not for that regarding illiteracy. However, only for equation (2) and (8) is the null

[5] Variable expressions ending with (-x) indicate that a lag of x years of the variable has been used.

hypothesis of no cross-section dependence satisfied. Therefore time dummies are not needed in equation (2). In order to avoid cross-section dependence of the other equations, in the last column of Table 2 we have added a difference GMM estimator suggested by Sarafides and Wansbeek (2010: section 5.2) for this problem. It takes variables as deviations from the time-specific averages and avoids cross-section dependence in the equation for illiteracy.

The five-year growth rate of aid per capita, increases life expectancy in regressions (1) and (2), in the latter instrumented with its own one-period lag. As we have T = 36, the expected bias in the lagged dependent variable is less than 1/36 and therefore the fixed-effect estimate is usually also held to be acceptable; these are very similar for both variables. For equation (4), using FMOLS, the rural percentage of the population reappears from the preliminary fixed-effects regressions of Table A.2. Equations (1) - (4) show that the growth of aid increases that of life expectancy. Equation (2) is preferred because it has no cross-section dependence.

For literacy the log level of aid matters. Instead of the squared value shown in regressions (5) and (6), we could also use the linear variable without change in sign and only a marginal difference in significance and size of the effect. The log level of aid reduces the growth rate of illiteracy, again with a long lag, suggesting that the education system is the channel where effects on young pupils are measured only in the literacy data when they are 15 years old. As an order of magnitude, 50 dollars of aid per capita reduces the growth rate of illiteracy by half a percentage point.[6] For the FMOLS estimate, the effect is roughly the same as for the fixed-effects estimate. The fixed-effects estimate (5), which does not rely on instruments and absence of second-order serial correlation and is consistent for T towards infinity, shows roughly the same result as the GMM equation (6). For the GMM difference method of Sarafides and Wansbeek (2010) the dimension of the variable is different and therefore coefficients are not comparable in size, but sign and significance are the same as before. In all equations aid reduces illiteracy in a statistically significant way.

5. Why do aid indicators differ so much across illiteracy regressions: a look at the non-linear lag structure using polynomial distributed lags

The regressions for the growth of life expectancy all use a similar five-year log difference of the aid variable and the results for the three data sets are very similar, with only some

[6] Running all the regressions for literacy instead of illiteracy, a number like 47 turns into 100-47= 53 etc. and under a log this is not neutral to details of the results, in particular non-linearities.

slight differences in the coefficients stemming from the longer time periods leading to different *N/T* ratios. As life expectancy and illiteracy have some upper or lower bound, their growth rates must phase out when a high life expectancy is reached. This leads to slight differences in the lagged dependent variables capturing the non-linearity, because the samples with a longer time period reveal more information about this limit and may come closer to it. On the other hand, the aid variables for the growth of illiteracy are very different from each other ~~in Tables 3 and 4~~for different time periods. This suggests a more complicated lag structure than used so far. In Table 3 we present results from using polynomial distributed lags (pdls). The first regression is a fixed-effects estimate ignoring potential endogeneity and using fixed effects with cross-section weights to deal with heteroscedasticity, called estimated generalized least squares. The second regression uses the lags of the variables as instrument (panel 2SLS) and cross-section weights. Using time dummies instead of cross-section weights leads to cross-section dependence in these two cases. In regression (3) we include the pdls in the system GMM of the orthogonal deviation mode. In the GMM estimate the current aid variable, log(1+*aid/pop*), and the first six (four) lags are statistically significant when using *t*-values of unity (two) as cut-off; the negative sum of lags has a *t*-value of –2.74. The other two estimates have effects from 20 lags. First, the coefficients are large and diminishing, then they have a phase of essentially zero, and later they are negative again. The sum of coefficients for the lags is about equally large for the first two regressions with weighted variables. For GMM the dimension of the variable is changed by taking orthogonal deviations and de-meaning. Similarly, the long-run effects differ across the regressions. In all cases it is safe to say that there is a statistically significant negative sum of coefficients for the lags, indicating that aid reduces the growth of illiteracy. Size and statistical significance of coefficients changing with the lags is another possible explanation for why the literature finds various results, besides the one given above emphasizing dynamics and earmarked disbursement data. Results regarding more detailed aspects of GMMSYS can be found in Ziesemer (2012).

<TABLE 3 near here>

6. Simulations: How strong are the aid effects?

The long lags of the previous section have not been taken into account in the literature. With 20 lags at work, which have short-run effects cumulating over time because of the lagged dependent variable, it is not immediately clear how strong the effects of aid are. Even without long lags the lagged dependent variables cause cumulation of aid effects over time. In order to explore the strength of the aid effects, we run simulations. For life expectancy we use the GMMSYS equation (2) in Table 2 and for illiteracy the two-stage EGLS equation in Table 3, because both have cross-section independence. To be able to feed these equations with values for their respective aid and GDP variables, we run an autoregressive regression of log(1+*aid/pop*) on a one-year lag with cross-section and time fixed effects and a similar one for GDP per capita. As the observations go from 1961 to 2010, $T = 50$ and we do not need to use IV methods. Fixed effects indeed vanish when we take one-year differences. The result is[7]

$$LOG(1+AID/POP) = 0.78 + 0.7995\ (LOG(1+AID(-1)/POP(-1))) + \varepsilon_t$$

Equation (2) of Table 2 for life expectancy has only aid as right-hand variable and lagged dependent variables in differences or levels. For the second equation in Table 3 for illiteracy we also need the autoregressive process for the log(*GDP*) variable. The autoregressive process we use is[8]

$$\begin{aligned} LOG(GDP) &= 0.257 + 0.9545 LOG(GDP(-1)) + 0.000685t + u_t \\ u_t &= 0.256u_{t-1} + 0.08u_{t-2} + 0.094u_{t-3} \end{aligned}$$

To the standard growth equation we add an autoregressive process of third order. In order to start the four difference equations running forward, we need initial values. We construct them by regressing each of the dependent variables on a constant and a linear or quadratic time trend. Then the baseline simulation can be obtained.

In the baseline scenario, 1+*aid/pop* converges to a yearly growth rate of zero, which it has also had since the 1980s in loess-fit regressions. The five-year growth rate of life expectancy converges to about 0.0226. As this is for low-income countries, there

[7] Period 1961–2010: 66 countries; 2894 observations; period SUR (PCSE) standard errors and covariance (d.f. corrected). Adjusted R-squared: 0.867. S.E. of regression 0.42. Estimation method: panel-estimated least squares with cross-section fixed effects and time dummies. Significance for both coefficients is $p = 0.0000$.

[8] Period 1964–2010: 61 countries; 2182 observations; period SUR (PCSE) standard errors and covariance (d.f. corrected). Adjusted R-squared 0.994. S.E. of regression 0.062. Significance for all coefficients is at least $p = 0.001$. Estimation method: panel-estimated weighted least squares with cross-section fixed effects. The long-run growth rate of this process is 1.5%.

is not yet a decrease in the growth rates in the data. Illiteracy falls below 1% around 2110 and then converges to, but never reaches, zero.

In the policy scenario for life expectancy, we add 0.1 (ten percent) to the five-year growth rate of 1+*aid/pop* from 1990 onwards, raising the five-year growth rate of life expectancy from 2.26% to 2.44%. The result is that the growth rate of life expectancy with this policy divided by that without policy is 1.08 in the long run and 1.13 ten years after the first increase; the difference between growth rates is about 0.0018. Of course, this then has cumulative effects on life expectancy. The ratio of the level of life expectancy with and without policy runs from unity 1990 to 1.04 in 2100 when people will be 89 years old with aid increase, instead of 85.4 without.

In the policy scenario for illiteracy, we multiply each aid variable log(1+*aid/pop*) by 1.01 from 1978 onwards. This corresponds to a 3.7 to 4% higher value of aid per capita, which is between $32 and $48 in the baseline for each period. Through this policy, illiteracy falls over time to 93% of its baseline value in 2100. This cumulated effect stems from the fact that the negative growth rate of illiteracy of the policy scenario divided by the baseline value is roughly 1.02, meaning that the falling growth rates fall 2% more quickly if aid is 4% higher.

These impacts of aid policy on the growth rates of life expectancy and illiteracy are not overwhelmingly large, but, given the well-known difficulties of enhancing growth rates in general, they are far from negligible.

7. Conclusions

This paper has four new major results. First, it has shown in the survey that aid can be effective in education and health. When earmarked aid is used, disbursement data lead mostly to statistically significant expected results, whereas commitment data do not. Panel data models, if using lagged dependent variables, also yield expected significant results unless commitment data are used. By implication, one should use the more adequate estimation method of dynamic panel data models and disbursement data, because undisbursed payments can hardly have any effect on health and literacy.

Second, in our own empirical research we find that lag structures and fixed effects suggest using the growth rates of life expectancy and illiteracy as the dependent variable, whereas the literature, with the exception of Bhaumik (2005) and Gillanders (2011), has used levels.

Third, whereas development aid per capita in the form of growth rates has a positive impact on the growth rate of life expectancy for our panel of countries, as others found earlier, for illiteracy we find that polynomial distributed lags should be used, because the great variety of results in the literature and our own regressions is most probably due to the fact that only current or one-period-lagged variables are used but higher lags are ignored in the literature.

Fourth, selecting among several regressions those that do not show cross-section dependence, which has not hitherto been tested in the literature, we analyse the order of magnitude of a permanent increase to the growth rate or level of aid in simulations, whereas the literature (with the exception of Gillanders 2011) relies only on sign and statistical significance.

The result of our analysis, taking the four points together, is that dynamic panel data models, applied to the growth rates of life expectancy and illiteracy, show an important role of lag structures and lead to non-negligible effects of aid that cumulate over time provided disbursement data are used.

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Appendix A: Data and preliminary fixed-effects regressions

List of countries

East Asia and Pacific: Cambodia; Indonesia; Korea, Dem. Rep.; Lao PDR; Mongolia; Myanmar; Papua New Guinea, Solomon Islands; Vietnam.

Europe and Central Asia: Armenia; Azerbaijan; Georgia; Kyrgyz Republic; Moldova; Tajikistan; Ukraine; Uzbekistan.

Latin America and Caribbean: Haiti; Nicaragua.

Middle East and North Africa: Yemen, Rep.

South Asia: Afghanistan; Bangladesh; Bhutan; India; Nepal; Pakistan.

Sub-Saharan Africa: Angola; Benin; Burkina Faso; Burundi; Cameroon; Central African Republic; Chad; Comoros; Congo, Dem. Rep.; Congo, Rep.; Côte d'Ivoire; Equatorial Guinea; Eritrea; Ethiopia; Gambia, The; Ghana; Guinea; Guinea-Bissau; Kenya; Lesotho; Liberia; Madagascar; Malawi; Mali; Mauritania; Mozambique; Niger; Nigeria; Rwanda; São Tomé and Principe; Senegal; Sierra Leone; Somalia; Sudan; Tanzania; Togo; Uganda; Zambia; Zimbabwe.

<TABLE A.1 near HERE>

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Table 1	**Literature structure**									
Publication	*social indicator*	*aid form (a)*	*com., disb. (b)*	*countr*	*years*	*ldv*	*est. Meth.*	*exp.sign*	*signif.*	*Remarks*
Arndt et al. (2011)	life expectancy	total, pc	-	58	1970-200	no	IPWLS	yes	yes	multi-eq. cross sec. model
Bhaumik (2005)	infant mortality	total	-	36-7	1990-200	no	FELS	yes	yes	variables differenced
	primary compl. rate	total	-	36-7	1990-200	no	FELS	yes	yes	variables differenced
Boone (1996)	(c)	total aid/GNP	-	96	1970-199	no	OLS, IV, FELS	yes	no	10 year averages of data
Burguet, Soto (2012)	under-5 mortality	infect. disease aid	disbursed	130	2000-201	no	2SLS	yes	yes	yearly data
Burnside, Dollar (1998, 2000)	infant mortality	total*policy	-	56	1970-199	no	2SLS	yes	yes	4 year averages
Chauvet et al. (2008)	u5 & infant mort.	health aid	disbursed	98	1987-200	no	2SLS	yes	yes	3 year average
D'Aiglepierre, Wagner (2010)	prim. Compl. Rate	aid f. Prim. Educ.	commit., disb.	46-88	1999-200	no	FELS, FEIV	yes	yes	3 year average
Dreher et al. (2008)	primary enrolm.	educ aid, total	commit., disb.	94	1970-200	yes	system GMM	yes	yes, no	5 year averages,
Feeny, Quattara (2013)	immunizations	health aid	disbursed	109	1990-200	no	basic, sysGMM	yes	yes	yearly
Fielding et al. (2006)	infant mortality	total, pc	-	48	-	no	sim.eq. Sys	yes	yes	cross-section regr.
Fielding et al. (2006)	schooling	total, pc	-	48	-	no	sim.eq. Sys	yes	no	quintile and survey years
Gomanee et al. (2005a)	infant mortality	total aid/GDP	-	38	1980-199	no	OLS, quantile	yes	yes	3 and 4 year average
Gomanee et al. (2005b)	infant mortality	total aid/GDP	-	104	1980-200	no	FELS	yes	yes	4 and 5 year average
Gillanders (2011)	life expectancy	total aid pc	-	31	1973-200	yes	PFELS	yes	yes	PVAR model
Gross (2003)	life expect., literacy	total aid pc	-	65	1960-200	yes	FELS	yes	yes	5 year averages,
Gyimah-Brempong, Asiedu (2008)	prim.compl.rate	earmarked	disbursed	90	1990-200	yes	Arellano-Bond	yes	yes	3 year average
Gyimah-Brempong, Asiedu (2008)	infant mortality	earmarked	disbursed	90	1990-200	yes	Arellano-Bond	yes	yes	3 year average
Hudson (2015)	prim. compl. rate	social infra/other	disbursed	120	2002-09	no	FELS	yes/no	yes/no	yearly
Masud, Yontcheva (2005)	illiteracy	bilateral, NGO aid	committed	54-76	1990-200	no	random effects	no	no	yearly data
Masud, Yontcheva (2005)	infant mortality	NGO	disbursed ?	49-58	1990-200	no	fixed, random eff	yes	yes/no	yearly data
Michaelova, Weber (2004)	primary enrolm.	education aid	disbursed	42-76	1970-200	yes	Arellano-Bond	yes	yes	annual or 5 year averages
Mishra, Newhouse (2009)	infant mortality	health aid, total	commited	118	1973-200	yes	system GMM	yes	yes, no	5 year averages,
Mukherjee, Kizhakethalckal (2013	infant mortality	health aid	disbursed	110	1978-200	no	semiparametric	yes	yes, no	4 year averages
Pickbourn, Ndikumana 2013	several (g)	health, educ. aid	disbursed	65, 75	1975(80)-	mix	several	yes, if ldv	yes, if ldv	yearly
Williamson (2008)	5 health indicators	earmarked, pc	committed (f)	208	1973-200	no	FE, IV	mixed	no	5 year averages,
Wilson 2011	u5, inf., life exp.	dev. ass. health	committed	84	1975-200	yes	Arellano-Bond	mixed	no	5 year averages,
Wolf (2007)	(d)	(e)	com.; disb.?(f)	41-10	1980-200	no	OLS	mixed	mixed	40-110 observations
Yogo and Mallaye (2014)	prim. compl. Rate	education aid	disbursed	35	2000-201	no	2SLS	yes	yes	various
Yogo and Mallaye (2015)	child mortality, HIV	health aid	disbursed	34	1990-201	yes	GMMSYS diff	yes	yes	4 year averages
Ziesemer (2011a)	literacy	total aid/GDP	-	30	1985-200	yes	FELS	yes	yes	yearly data, variables differenced

(a) The expressions total, overall and aggregte aid are used synonymously in the literature. Most papers do not report whether total aid is disbursed or committed.
(b) The distinction between disbursed and committed aid appears in the literature only for earmarked aid, not for overall aid.
(c) Infant mortality, primary schooling, life expectancy,
(d) Sanitation, water, infant and under-5 mortality, primary completion rates and youth literacy
(e) Aid/GNI and its coefficient of variation, earmarked aid and its interaction with control of corruption
(f) This is also based on information in Michaelova (2004), who states that there is information on disbursements only for 42 countries.
(g) maternal mortality, health index, education index

Table 2 The impact of aid on life expectancy and illiteracy

Dependent variable	*log(LIFE)-log(LIFE(-5))*					*log(ILL)-log(ILL(-5))*				
Estimation Method	FELS	GMMSYS	OLS	FMOLS		FELS	GMMSYS	OLS	FMOLS	GMMD
Regressors	(1)	(2)	(3)	(4)	*Regressors*	(5)	(6)	(7)	(8)	(9)
Constant	0.027	-	0.022	-	Constant	0.002	-	0.001	-	-
	(0)***	-	(0)***	-		(.738)	-	(.868)	-	-
log(LIFE(-5))-log(LIFE(-10))	0.588	0.821	0.717	0.723	log(ILL(-1))-log(ILL(-6))	2.202	2.070	1.710	1.935	-5.428
	(0)***	(0)***	(0)***	(0)***		(0)***	(0)***	(0)***	(0)***	(0.099)*
$(\log(LIFE(-5))-\log(LIFE(-10)))^2$	0.563	2.463	0.431	0.703	log(ILL(-2))-log(ILL(-7))	-1.273	-1.138	-0.698	-1.035	4.983
	(0)***	(0)***	(0)***	(0)***		(0)***	(0.008)***	(0.06)*	(0)***	(0.05)**
$(\log(LIFE(-5))-\log(LIFE(-10)))^3$	-4.125	-6.969	-4.736	-4.569	$\log(1+AID(-10)/POP(-10))^2$	-0.0006	-0.00063	-0.000013	-0.000562	-0.0064
	(0)***	(0)***	(0)***	(0)***		(.003)	(0.004)***	(.935)	(0.005)***	(0.036)**
log(LIFE(-10))-log(LIFE(-15))	-0.492	-0.616	-0.451	-0.431	log(GDP(-2))-log(GDP(-7))	-	-	-	-	0.096
	(0)***	(0)***	(0)***	(0)***		-	-	-	-	(0.046)**
log(1+AID/POP)-log(1+AID(-5)/POP(-5))	0.007	0.012	0.006	0.009						
	(0.003)***	(0.02)**	(0.008)***	(.0001)***						
rural-rural(-5)	-	-	-	-0.002						
	-	-	-	(0.009)***						
log(GDP(-1))-log(GDP(-6))	-	-	-	0.02						
	-	-	-	(0.002)***						
Period	1975–2010	1981–2010	1975–2010	1976–2010		1977–2003	1979–2003	1977–2003	1978–2003	1978–2003
Countries/periods (N/T)	52/36	52/30	52/36	48/35		45/27	42/25	45/27	41/26	41/26
Total observations	1723	1447	1723	1378		1035	951	1035	988	810
Adj.R-sq.	0.441	-	0.372	0.433		0.918	-	0.752	0.874	-
Standard error of regression	0.039	0.050	0.042	0.040		0.020	0.021	0.035	0.022	0.031
Cross-section dependence test p-value	0.000	0.599	0.000	0.000		0.000	0.000	0.000	0.000	0.436

Notes

p-values in parentheses: * for 10% level, ** for 5%, *** for 1% level.

Estimation methods: fixed effects, ordinary and fully modifeid OLS (FELS, OLS, FMOLS); General method of moments for systems and differences (GMMSYS, GMMD)

In all regressions: Yearly data, time-fixed effects (except (2) and FMOLS). Period SUR (seemingly unrelated regression) panel corrected standard errors & covariance (d.f. corrected).

GMMSYS in (2) uses the orthogonal deviation method with 2SLS instrument weighting matrix.

GMM in (5) uses first differences, but instruments in levels, both de-meaned for time-specific averages of variables.

Instrument specification for equation (2): c, log(LIFE(-7))-log(LIFE(-12)), $(\log(LIFE(-7))-\log(LIFE(-12)))^2$,
$(\log(LIFE(-7))-\log(LIFE(-12)))^3$, log(LIFE(-15))-log(LIFE(-20)), log(1+AID(-1)/POP(-1))-log(1+AID(-6)/POP(-6)).

Instrument specification for equation (5): log(ILL(-2))-log(ILL(-7)), log(ILL(-3))-log(ILL(-8)) , $\log(1+AID(-10)/POP(-10))^2$, time dummies for all periods, all in levels.

Instrument specification for equation (8): (LOG(ILL(-2))-LOG(ILL(-7))-FTILL05(-2)), (LOG(ILL(-3))-LOG(ILL(-8))-FTILL05(-3)),
(LOG(1+AID(-10)/POP(-10))^2-FTAID10SQ(-0)), (LOG(GDP(-2))-LOG(GDP(-7))-FTGDPGR(-2)), time dummies.

With instrument rank equal to the number of estimated parameters there is no overidentification and the Hansen J-statistic is zero.

In GMMD variables are taken as deviation from time-specific averages denoted as FT.

Table 3	**Lag structure of Aid effects on illiteracy growth**						
Regression	(b)	Panel EGLS		Panel TSLS (c)		GMMSYS (d)	
		coeff.	t-stat.	coeff.	t-stat.	coeff.	t-statistic
C		0.006	2.83	0.006	2.37	-	-
log(ILL(-1))-log(ILL(-6))		0.984	105.0	0.970	90.13	0.7661	7.36
log(GDP(-2))-log(GDP(-7))		0.002039	2.38	2.0E-03	2.26	-	-
PDL01		-0.000080	-1.91	-1.4E-04	-3.31	-0.0002	-0.66
PDL02		-0.000034	-2.14	-3.8E-05	-2.43	-0.0008	-2.35
PDL03		-0.0000011	-0.99	2.8E-07	0.26	-	-
PDL04		0.0000004	1.66	4.0E-07	1.75	-	-
lag of aid (a)							
0		-0.00023	-3.27	-0.00013	-0.80	-0.0073	-1.51
1		-0.00014	-3.83	-6.20E-05	-0.59	-0.0083	-3.37
2		-6.90E-05	-4.52	-1.90E-05	-0.27	-0.0101	-22.27
3		-2.30E-05	-4.16	5.50E-06	0.10	-0.0102	-4.29
4		5.00E-06	-2.50	1.40E-05	0.25	-0.0097	-2.05
5		1.7E-05	-1.39	8.90E-06	0.15	-0.0092	-1.30
6		1.6E-05	-0.87	-7.5E-06	-0.12	-0.0092	-0.97
7		3.1E-06	-0.70	-3.3E-05	-0.56	-	-
8		-1.9E-05	-0.80	-6.5E-05	-1.22	-	-
9		-4.7E-05	-1.16	-1.0E-04	-2.15	-	-
10		-8.0E-05	-1.80	-1.4E-04	-3.31	-	-
11		-1.2E-04	-2.50	-1.8E-04	-4.33	-	-
12		-0.00015	-2.91	-2.1E-04	-4.79	-	-
13		-0.00018	-3.06	-2.4E-04	-4.80	-	-
14		-0.00021	-3.13	-2.6E-04	-4.66	-	-
15		-0.00023	-3.24	-0.00027	-4.55	-	-
16		-0.00024	-3.42	-0.00027	-4.51	-	-
17		-0.00024	-3.67	-0.00026	-4.51	-	-
18		-0.00023	-3.71	-0.00022	-4.32	-	-
19		-0.0002	-2.79	-0.00017	-3.20	-	-
20		-0.00015	-1.36	-9.60E-05	-1.30	-	-
Sum of Lags		-0.0025	-5.53	-0.00271		-0.04537	-2.7362
Adjusted R-squared			0.999		0.999		-
Standard error of estimation			0.019		0.018		0.035
Sum of squared residuals			0.244		0.236		1.206
Observations:		743		877		1016	
Countries		40		40		41	
Period		1980–2003		1980–2003		1978–2003	
Cross-section dependence test p-value			0.79		0.9355		0

Notes to Table 5

Dependent variable: log(ill)-log(ill(-5))

Estimation methods: Estimated Generalized Least Squares (EGLS); Two-Stage Least Squares (TSLS)
Generalized Method of Moments for Systems (GMMSYS).

(a) Aid variable is (log(1+AID/POP); lag used as instrument. Pdl is polynomial distributed lag parameter.

(b) Cross-section weights used in first and second regression and therefore no time dummies.

(c) Instrument specification: C, log(ILL(-2))-log(ILL(-7)), log(GDP(-2))-log(GDP(-7)), Polynomial distributed lag (pdl) of third degree for log(1+AID(-1)/POP(-1)) with 20 lags.

(d) 46 countries. Orthogonal deviations. 2SLS instrument weighting matrix. Coefficients of time dummies not shown. Instrument specification: c, log(ILL(-2))-log(ILL(-7)), PDL(log(1+AID(-1)/POP(-1)), 6 lags, polynomial of the 1st degree), time dummies. As there is one IV for each regressor there are no overidentification constraints and the Hansen J statistic is zero. Using the one-period-lagged pdl as instrumental variable yields almost identical results.

Table A.1: Descriptive Statistics, individual samples

(a) Data for 65 countries, 1960-2000 in five-year averages							
	AID	GDP	HEALTH	ILL	LIFE	PEE	RURAL
Mean	41.58	447.62	4.30	52.47	50.12	4.00	74.32
Median	29.64	350.53	4.05	58.33	48.14	3.09	77.10
Maximum	478.78	2492.38	12.68	94.25	73.48	41.78	97.88
Minimum	0.55	95.46	1.63	0.42	32.45	0.02	30.56
Std. Dev.	46.82	336.17	1.83	26.38	9.50	4.23	15.33
Skewness	3.75	2.63	1.48	-0.55	0.71	5.55	-0.74
Kurtosis	26.34	12.51	6.44	2.26	2.70	42.98	2.93
Observations	418	365	142	357	481	290	501
(b) Data for 65 countries, 1960-2001, yearly							
	AID	GDP	HEALTH	ILL	LIFE	PEE	RURAL
Mean	29.84	432.17	4.17	49.95	50.49	3.88	74.69
Median	15.40	355.50	3.90	53.65	48.20	3.09	77.20
Maximum	638.00	2110.00	12.20	94.30	74.40	41.80	97.80
Minimum	0.00	49.30	0.86	0.38	31.20	0.27	32.00
Std. Dev.	42.79	278.94	1.69	25.51	10.09	3.57	15.20
Skewness	4.71	1.96	1.09	-0.45	0.63	5.14	-0.72
Kurtosis	42.92	8.48	4.93	2.23	2.43	42.60	2.87
Observations	2347	1946	591	1696	1180	760	2666
(c) Data for 65 countries, 1960-2010, yearly							
	AID	GDP	HEALTH	ILL	LIFE	PEE	RURAL
Mean	67.89	455.22	5.52	47.99	51.24	4.09	72.61
Median	47.33	335.74	5.18	51.27	49.84	3.39	74.62
Maximum	928.13	8811.21	19.31	94.25	73.78	49.52	98.00
Minimum	-0.18	57.78	0.01	0.00	26.82	0.42	31.90
Std. Dev.	81.17	518.75	2.45	26.27	9.54	3.70	15.33
Skewness	3.36	9.33	1.52	-0.35	0.27	7.00	-0.58
Kurtosis	20.37	128.59	7.01	2.05	2.30	71.75	2.61
Observations	2984	2426	1006	1568	2652	589	3366

The three panels differ in terms of their base years for some variables.

Table A.2	Preliminary panel fixed effects estimates					
Dependent variable	*log(LIFE)-log(LIFE(-5))*			*ILL-ILL(-5)*		
Regressors	(1)	(2)	(3)	(4)	(5)	(6)
C	-0.019	-0.657	0.146	4.399	3.429	-2.363
	(0.015)**	(0)***	(0)***	(0.001)***	(0)***	(0.004)***
HEALTH-HEALTH(-5)	0.121	0.024	-	-	-	-
	(0.002)***	(0.015)**	-	-	-	-
$HEALTH^2$-$HEALTH(-5)^2$	-0.015	-0.003	-	-	-	-
	(0.002)***	(0.013)**	-	-	-	-
HEALTH(-1)	-	-	-0.003	-	-	-
	-	-	(0.09)*	-	-	-
log(LIFE)-log(LIFE(-1))				-2.235		
				(0.023)**		
log(LIFE(-5))-log(LIFE(-10))	-29.209	-12.330	-0.182	-	-	-2.235
	(0)***	(0.001)***	(0.03)**	-	-	(0.013)**
log(LIFE(-5))2-$\log(LIFE(-10))^2$	3.773	1.581	-	-	-	-
	(0)***	(0.001)***	-	-	-	-
log(AID(-0))-log(AID(-5))	-	0.017	0.011	-	-	-
	-	(0.052)*	(0)***	-	-	-
$(\log(AID)-\log(AID(-1)))^2$	-	-	-	-0.250	-	-
	-	-	-	(0)***	-	-
log(AID(-1))2-$\log(AID(-6))^2$	-	-0.003	-	-	-	-
	-	(0.03)**	-	-	-	-
log(AID(-5))-log(AID(-10))	0.025	-	0.007	-	-	-
	(0.074)*	-	(0)***	-	-	-
$(\log(AID(-5))-\log(AID(-10)))^2$	-	-	-	-	-0.016	-0.189
	-	-	-	-	(0.047)**	(0.006)***
NINET*log(AID(-1))-log(AID(-2))	-	-	-	-	-0.025	-
	-	-	-	-	(0.052)*	-
NINET*log(AID(-5))-log(AID(-10))	-	-	-	-0.130	-	-
	-	-	-	(0.001)***	-	-
RURAL(-0)	-	0.010	-0.001	-0.094	-0.052	-
	-	(0)***	(0.001)***	(0)***	(0)***	-
log(GDP(-1))-log(GDP(-6))	-	0.042	0.013	-	-	-
	-	(0.028)**	(0.067)*	-	-	-
(ILL(-5))-(ILL(-10))	-	-	-	0.337	0.625	0.296
	-	-	-	(0)***	(0)***	(0.011)**
(ILL(-10))-(ILL(-15))	-	-	-	-	0.294	-
	-	-	-	-	(0.002)***	-
PEE(-5)	-	-	-	-	-	-1.194
	-	-	-	-	-	(0.001)***
log(PEE(-5))	-	-	-	-0.469	-0.126	-
	-	-	-	(0.005)***	(0.001)***	-
log(PEE(-10))	-	-	-	-0.382	-	0.653
	-	-	-	(0.012)**	-	(0.014)**
$\log(PEE(-5))^2$	-	-	-			1.796
	-	-	-			(0.001)***
$\log(PEE(-10))^2$	-	-	-			-0.372
	-	-	-			(0.007)***
Period	1990–2000	1995–2000	1996–2010	1975–2000	1985–2001	1980–2009
Data	5-year ave.	yearly	yearly	5-year ave.	yearly	yearly
Countries/periods (N/T)	42/2	54/5	48/15	36/5	46/17	20/7
Total observations	73	125	680	126	438	39
Estimation Method	FELS	FELS	FELS	FELS	FELS	FELS
Adjusted R-squared	0.821	0.864	0.660	0.948	0.981	0.995
S.E. of regression	0.025	0.021	0.029	0.399	0.239	0.148

TAble A.2 continued

Mean dependent variable	-0.002	-0.002	0.033	-4.979	-4.666	-5.111

p-values in parentheses; * for 10% level, ** for 5% and *** for 1%. Fixed effects estimations without any instruments.

Cross-section fixed effects and weights (PCSE) standard errors & covariance (d.f. corrected) in all regressions.

Lag notation for yearly variables. In regressions (1) and (4) the lag notations -5, -10 can be replaced by -1,-2 in terms of 5-year periods.

When adding time dummies to equation (2) 'rural' becomes insignificant, but other results change only marginally.

When adding time dummies to equation (3) the growth rate of the GDP per capita becomes insignificant; 'rural' changes sign if we take the growth rate out, and the constant becomes insignificant, but other results change only marginally. We have added a '1' to the aid variable in this equation in order to avoid a log of a non-positive variable.

Time dummies are redundant in equation (1) and do not change sign or significance for equations (4), (5).